



# A Machine-Learning Approach for Classifying Defects on Tree Trunks using Terrestrial LiDAR

Van-Tho Nguyen, Thiéry Constant, Bertrand Kerautret, Isabelle -  
Debled-Rennesson, Francis Colin

## ► To cite this version:

Van-Tho Nguyen, Thiéry Constant, Bertrand Kerautret, Isabelle - Debled-Rennesson, Francis Colin. A Machine-Learning Approach for Classifying Defects on Tree Trunks using Terrestrial LiDAR. Computers and Electronics in Agriculture, 2020, 171, pp.1-12. 10.1016/j.compag.2020.105332 . hal-02931277

**HAL Id: hal-02931277**

**<https://hal.science/hal-02931277>**

Submitted on 5 Sep 2020

**HAL** is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

# 1 A Machine-Learning Approach for Classifying Defects 2 on Tree Trunks using Terrestrial LiDAR

3 Van-Tho Nguyen<sup>a</sup>, Thiéry Constant<sup>a</sup>, Bertrand Kerautret<sup>b</sup>, Isabelle  
4 Debled-Rennesson<sup>c</sup>, Francis Colin<sup>a</sup>

5 <sup>a</sup>*Université de Lorraine, AgroParisTech, Inra, Silva, F-54000 Nancy, France*

6 <sup>b</sup>*Univ Lyon, Lyon 2, LIRIS, F-69676 Lyon, France*

7 <sup>c</sup>*Université de Lorraine, LORIA, UMR CNRS 7503, F-54506 Vandœuvre-lès-Nancy,*  
8 *France*

---

## 9 Abstract

Three-dimensional data are increasingly prevalent in forestry thanks to terrestrial LiDAR. This work assesses the feasibility for an automated recognition of the type of local defects present on the bark surface. These singularities are frequently external markers of inner defects affecting wood quality, and their type, size, and frequency are major components of grading rules. The proposed approach assigns previously detected abnormalities in the bark roughness to one of the defect types: branches, branch scars, epicormic shoots, burls, and smaller defects. Our machine learning approach is based on random forests using potential defects shape descriptors, including Hu invariant moments, dimensions, and species. The results of our experiments involving different French commercial species, oak, beech, fir, and pine showed that most defects were well classified with an average  $F_1$  score of 0.86.

10 *Keywords:* roundwood quality, random forests, standing tree grading

---

## 1. Introduction

Grading standing trees and roundwoods is a critical task in a wood supply chain before harvesting or processing in the wood industry (Fonseca, 2005). This question is especially concerned by the general trend towards digitization for forest wood-chain traceability, supply chain optimization, and transformation (Pickens et al., 1997; Lin and Wang, 2012; Gardiner and Moore, 2014; Müller et al., 2019). After the overall shape characterization defining material yield, and wood quality information coming from the cross-sectional ends in the case of roundwood, wood quality is mainly assessed from singularities of the bark surface. The occurrence of such singularities indicates local variations of the material properties generally corresponding to decreased normal distribution of the clearwood properties and characteristics, which detrimentally impact future products and their mechanical, physical or aesthetical functions. Nevertheless, the resulting grade made by an expert corresponds to a global assessment of the quality by taking many criteria into account through grading rules. After the attribution of the grade, the original causes are often forgotten.

Alternatives using X-ray computed tomography (CT) can be considered as reference methods for such a characterization (Li et al., 1996; Zhu et al., 1996; Aguilera et al., 2008; Colin et al., 2010b). On the one hand, CT can achieve good accuracy for defect recognition (up to 95%; Li et al. (1996)), detect the defects as small as 1 millimeter in diameter by manually placing plot markers along the tracks of knot (Colin et al., 2010b), or automatically detect knots (Longuetaud et al., 2012; Krähenbühl et al., 2012, 2016). Industrial solutions are proposed by several companies (Microtec, 2019; Jörg

Elektronik GmbH, 2019). On the other hand, CT has its own limitations with investment cost and the need to fell the tree and cut it into logs. Besides the fact that grading rules are mainly defined from external observations where bark is present, recent studies confirmed a strong correlation between internal and external defects (Thomas, 2009; Stängle et al., 2014; Racko, 2013; Pyörälä et al., 2018) with coefficients of determination ( $R^2$ ) greater than 0.6. From these results and practices, the question arose as to the use of three-dimensional (3D) technologies for describing the external envelope of trunks or logs with the objective of detecting bark surface defects.

LiDAR (Light Detection and Ranging) can measure objects in three dimensions through a technique in which a laser beam is emitted and the reflected light is received by a detector. The resulting product is a point cloud that contains the three spatial dimensions (x, y and z coordinates) of the scanned object. In forestry, terrestrial laser scanning (TLS) can provide information about an individual tree or a plot (Dassot et al., 2011). A variety of forestry applications have been developed in the last two decades. In particular, a number of studies has taken advantage of the potential of LiDAR for the replacement of conventional methods of measuring forest inventory parameters, such as tree height, diameter at breast height (DBH, trunk diameter measured at 1.3 m above ground level) (Hopkinson et al., 2004; Simonse et al., 2003), stand density, stand basal area, and volume for biomass assessment (Van Leeuwen and Nieuwenhuis, 2010; Yao et al., 2011; Dassot et al., 2012; Astrup et al., 2014).

On standing trees, there have been attempts to estimate tree quality criteria from TLS (Kankare et al., 2014; Blanchette et al., 2015), airborne

61 LiDAR (Maltamo et al., 2009; Luther et al., 2014; Kankare et al., 2014), or  
 62 both types of LiDAR (Van Leeuwen et al., 2011). The quality parameters  
 63 targeted in these works mainly concerned the overall shape of the timber:  
 64 ovality, curvature, taper, and the presence of branches. Research focused on  
 65 the detection of external defects are scarce (Schütt et al., 2004; Stängle et al.,  
 66 2014; Thomas et al., 2007; Kretschmer et al., 2013). Most of these studies  
 67 were dedicated to the detection of large and very obvious defects. Thomas  
 68 et al. (2007); Thomas and Thomas (2010) detected, on red oak and yellow  
 69 poplar, defects with a diameter greater than 7.5 cm and protruding by at  
 70 least 2.2 cm from the bark. Kretschmer et al. (2013) proposed an approach to  
 71 detect and manually measure the branch scars on Scots pine by highlighting  
 72 them on a 3D reconstruction of the bark surface: the bark surface is colored  
 73 based on the distance to a fitted cylinder surface corresponding to a trunk  
 74 part. The scars, with a diameter of at least 2 cm and protruding by at least  
 75 1.5 cm from the bark, were detected. Existing research on the automated  
 76 classification of defects on tree bark using TLS is even scarcer. Schütt et al.  
 77 (2004) presented a semi-automatic approach, based on a neural network, to  
 78 detect and classify wood defects using both range and intensity information  
 79 of TLS data.

80 In a previous work (Nguyen et al., 2016b), we successfully developed an  
 81 algorithm to detect the defects on trunks surface. Using a suitable spatial  
 82 resolution of the 3D data, the detection can segment potential defects with  
 83 a dimension as small as 1 cm and small protrusion on trunks of different tree  
 84 species. This important improvement was obtained from two major compo-  
 85 nents. First, the definition of the most relevant trunk centerline results from

86 a voting algorithm selecting the most frequent locations of the intersections  
 87 of the inward pointing normals to the surface. Secondly, the reference dis-  
 88 tance to the centerline is computed for each individual point by taking its  
 89 neighborhood into account. The computation of reference distance for each  
 90 individual point allows for more precisely detecting the abnormalities on the  
 91 bark than more global reference surface based on primitive fitting such as  
 92 cylinder (Schütt et al., 2004; Stängle et al., 2014; Kretschmer et al., 2013) or  
 93 circle (Thomas et al., 2007; Thomas and Thomas, 2010).

94     Returning to the main purpose of the work presented here, once potential  
 95 defects are detected, an automatic procedure must be able to assign them  
 96 to a defect type and to confirm their status. The main challenge in the  
 97 classification of these defects is to deal with the variability of their appear-  
 98 ance, even for the same type of defect. In the forestry domain, the defects  
 99 are often defined by the biological origin (Colin et al., 2010a) that leads to  
 100 a high intra-class variability and inter-class similarity. Figure 1 (c-f) and  
 101 (g-i) give examples of the intra-class variability between branch scars and  
 102 burls respectively. Inter-class similarity between an epicormic shoot and a  
 103 burl is shown in Figure 1 (b) and (g). Factors contributing to the intra-  
 104 class variability or inter-class similarity are the tree species, often linked to  
 105 the characteristics of its bark, the shape and the age of the defect and all  
 106 the history of its development in connection with the environment of the  
 107 tree. Facing this huge variability, a major difficulty is to build a representa-  
 108 tive database allowing the establishment of classification methods and their  
 109 testing especially in studying the feasibility of such an approach as in this  
 110 work. Several methods in the field of pattern recognition can be applied

111 to classify objects, such as neural networks (Bishop, 1995), support vector  
 112 machines (Cortes and Vapnik, 1995), random forests (Breiman, 2001), Bayes  
 113 classifier (Devroye et al., 1996), and deformable models (Terzopoulos and  
 114 Fleischer, 1988). Most approaches are based either on parametric models or  
 115 on machine-learning techniques. In the remote sensing domain, the machine-  
 116 learning supervised classifiers are widely used because they are more flexible  
 117 in handling the high variability in object appearance and are more robust  
 118 than model-based approaches (Niemeyer et al., 2014). In particular, random  
 119 forests are a supervised machine-learning method that is based on ensembles  
 120 of classification trees. Random forests exhibits many interesting properties,  
 121 such as high accuracy, robustness against over-fitting, noise or missing data  
 122 in the training set (Díaz-Uriarte and De Andres, 2006). Moreover, random  
 123 forests is a non-parametric method that does not require the information  
 124 on the distribution of data. These advantages make random forests a suc-  
 125 cessful classification method since its introduction by Breiman (2001). In  
 126 the domain of remote sensing, random forests were used in landcover clas-  
 127 sification or urban area classification from airborne LiDAR (Chehata et al.,  
 128 2009; Guo et al., 2011) or Landsat data (Yuan et al., 2005; Gislason et al.,  
 129 2006). In the forestry domain, random forests were used to accompany the  
 130 forest inventory, such as for biomass assessments (Mutanga et al., 2012), us-  
 131 ing airborne LiDAR. Othmani et al. (2013) used random forests to identify  
 132 the tree species from the analysis of tree bark pattern from the mesh derived  
 133 from TLS data. Random forests were used to assess the timber quality of  
 134 Scots pine by estimating tree properties, such as trunk diameters, tree height  
 135 and branch heights using the parameters computed from TLS data (Kankare

136 et al., 2014).

137 The main objective of this work is to classify the potential defects de-  
138 tected on trunk surface by previously developed algorithms (Nguyen et al.,  
139 2016b). The other objective is to evaluate the performance of a robust and  
140 commonly used machine-learning algorithm, random forests, for the classifi-  
141 cation of bark singularities. The targeted types of defects are branch, branch  
142 scar, burl, and small defects including sphaeroblast, bud cluster, and picot.  
143 These types were chosen to represent the existing diversity of defects; never-  
144 theless, some were grouped because of the difficulty in distinguishing them  
145 given their size or shape. We aimed to develop a method that works on the  
146 common commercial tree species, including hardwood species like sessile oak  
147 (*Quercus petraea* (Matt.) Liebl.), European beech (*Fagus sylvatica* L.), and  
148 wild cherry tree (*Prunus avium* (L.) L.), or conifers such as silver fir (*Abies*  
149 *alba* Mill.), Scots pine (*Pinus sylvestris* L.), and Norway spruce (*Picea abies*  
150 (L.) H.Karst.). Here a special focus is given to the results concerning oak and  
151 European beech two hardwood species that have very different bark rough-  
152 ness, defect types and shapes. The first species has a furrowed bark and  
153 its most common defect types are burl and picot. The second has smooth  
154 bark and the most common defect type is branch scar with an eyebrow (or  
155 "Chinese mustache") shape.

## 156 2. Materials and Methods

### 157 2.1. Defects on trunk surface

158 Several defects on the trunk surfaces can be caused by exogenous factors  
159 depending on their environment, such as heat, frost, other trees, animals, and



160 human beings. Our study focused on the most frequent source of defects,  
161 which arises from tree branching. Branching defects are the result of the  
162 development and growth of the tree. Their scars are associated generally  
163 with protruding regions that result from the inclusion of the defect by the  
164 radial growth of the trunk. More precise definitions of what we considered  
165 as a branching defect were as follows:

- 166     • A sequential branch was a branch that emerged after a winter's rest of  
167       the original bud.
- 168     • An epicormic branch was a branch that emerged after several winters  
169       from a latent bud.
- 170     • A branch scar was a track of a branch, either sequential or epicormic  
171       that maintains when this branch has died and has been degraded.  
172       Branch scars on hardwood were often referred to as bark distortions.
- 173     • A bud was a miniature leafy shoot protected by a covering of scales.
- 174     • A burl was a group of juxtapositional defects of one or more type, such  
175       as bud, picot, branch or branch scar. By definition, a burl could have  
176       a great variability in shape and size and composition.
- 177     • A bud cluster was a limited group of buds of less than six buds.
- 178     • A sphaeroblast was a bud whose base produces xylem that progressively  
179       covers the apical meristem of the bud (mainly on beech) (Fink, 1999).
- 180     • A picot was a small branch with its apex naturally pruned. Picots are  
181       defined and illustrated in Colin et al. (2010b).

182 Typical defects on trunk surface were represented in Figure 1. These  
183 defects were characterized by a large intra-class variability in size and shape.  
184 For instance, burls could range from a large bud cluster with at least six  
185 buds to a very extended mass of buds, picots, short or long branches with a  
186 diameter of several tens of centimeters.

187 The impact of defects on the wood quality depended on their type and  
188 dimension. For defects of the same type, larger defects had a more important  
189 impact than smaller ones. In general, the most penalizing defects were branch  
190 scar, branch and burls. The impact of small defects such as bud cluster,  
191 sphaeroblast and picot is small, but some had to be taken into account in  
192 the highest quality class.

## 193 *2.2. Methodology*

194 The steps of our method are presented in Figure 2. After their acquisition,  
195 the TLS data were preprocessed to obtain a smooth mesh corresponding to a  
196 trunk portion. Next, the potential defects were detected by using a segmen-  
197 tation algorithm, which is an improved version of the previously published  
198 work (Nguyen et al., 2016b) and is summarized in section 2.5. Then, the po-  
199 tential defects were classified into defect types using trained random forests.  
200 Finally, the results were visualized by various colors on the mesh according  
201 to the defect type. The classification was validated by comparing the results  
202 with the ground-truth labels classified by an expert on the trunks before  
203 the TLS scans were carried out. Two methods were used by the expert to  
204 mark the defect type. The first method used small distinctive shape pinned  
205 in the vicinity of the defect. Thus, the defect type was recognized in the  
206 reconstruction of trunk surface. The second method measured the coordi-

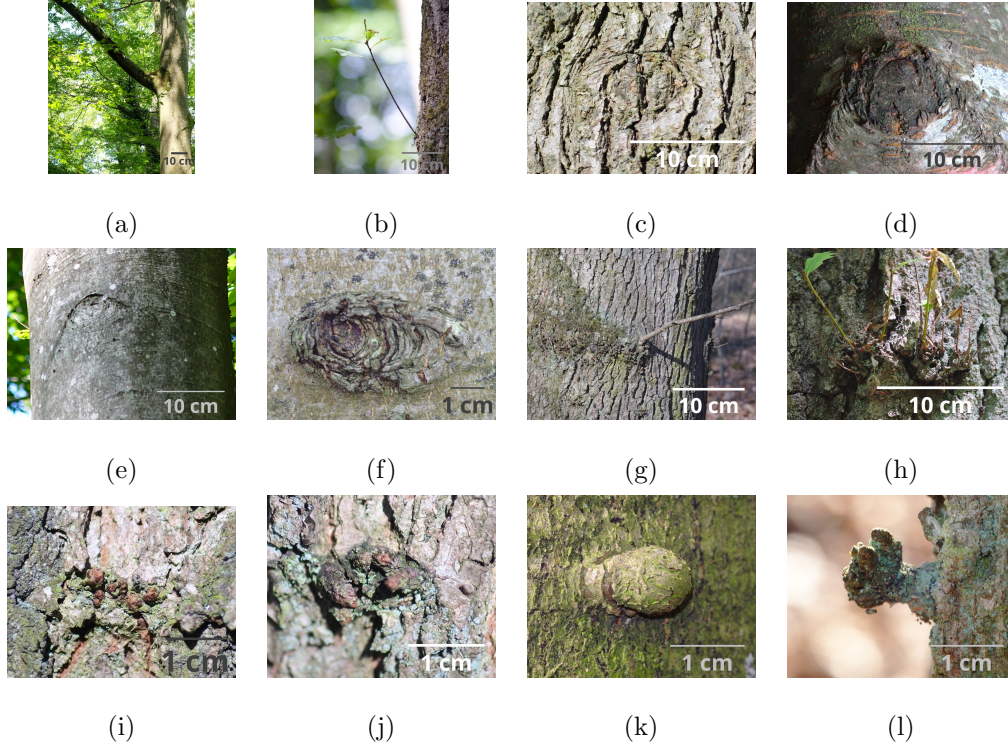


Figure 1: Some illustrations of the defect types considered in this study. (a, b) branches: sequential branch (a), and epicormic shoot (b); (c-f) branch scars: on oak (c), on wild cherry (d), on beech (e), and on beech (f); (g, h) burl: consisting of buds and an epicormic shoot (g), buds and short epicormic shoots (h), and buds (i); small defects: (j) bud cluster, (k) sphaeroblast, and (l) picot.

207 nates of the defects by a local coordinate  $(l, z)$  system on the trunk with  $l$   
 208 the position along a longitudinal axis  $Oz$  and  $l$  the signed arc length between  
 209 the reference axis and the defect center. Two ping-pong balls were used to  
 210 define the axis. A dedicated software was developed to recover the same  
 211 coordinate system on the reconstruction of trunk surface, which allowed for  
 212 measuring the defect coordinates and comparing with the ground truth. The

213 ground truth contained all of the defects with a diameter equal or greater  
 214 than 0.5 centimeters and from 0.5 to 2 meters or 5 meters depending on the  
 215 distribution of defects.

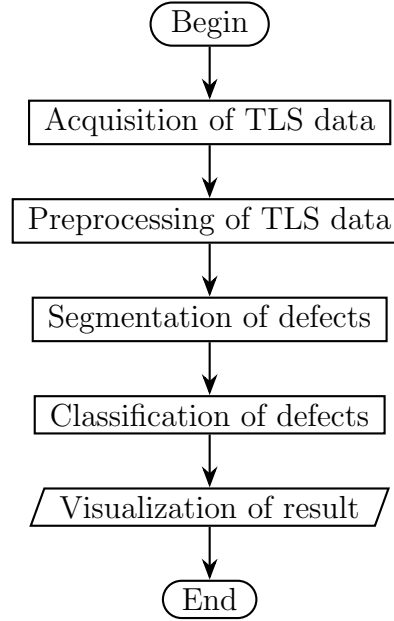


Figure 2: Overview of the processing flow for classifying the surface defects onto a trunk.

### 216 2.3. Acquisition of TLS data

217 The tree trunks exhibiting different defects were measured with a Faro Fo-  
 218 cus 3D X130 laser scanner in the Champenoux and Haye forests in the Grand-  
 219 Est region of France. To detect small defects, we chose a high-resolution set-  
 220 ting and put the scanner close to the trunk. The utilized resolution was one  
 221 half of the maximum value and the distance from the scanner to the trunk  
 222 was approximately 3-4 meters. With this setting, the angular resolution of  
 223 the scan was  $0.018^\circ$  in both horizontal and vertical directions, and the result-  
 224 ing distance between two neighboring 3D points on the trunk surface in the

point cloud was around 1 millimeter. Such settings ensured a high-quality description of the defects limiting the laser beam inclination resulting from the defect height and the distance to the tree. The trees were sampled according to several criteria. Among the main commercial species, selected trees must have a sufficiently large diameter (see Table 1) and represent a variability in bark roughness, which depends on the species and the age of the trees. In agreement with these criteria, we scanned 26 trees: nine sessile oaks, eight European beeches, three wild cherries, two Scots pines, three silver firs, and one Norway spruce. These scans were divided into 2 sets. One was used to train the random forests and another was used to test the method efficiency (Table 1). The training set contained 425 defects from 16 trees and the test set contained 183 defects from 10 trees.

During this acquisition step, the objective was to maximize the number and type of defects per scan; thus, trunks were either scanned entirely with four scans from suitable points of view or partially with one or two scans on just one side. If the trunk was scanned from multiple points of view, the scans were merged into a single file per tree to recover the 3D view of the trunk. The registration was performed by the standard procedure available in the FARO SCENE software (Faro Technologies Inc., Lake Mary, FL), through the use of spheres.

#### 2.4. *Preprocessing of TLS data*

LiDAR data are generally noisy, and the first processing step aimed to manage noise for enhancing the recognition rate. It included the reduction of noise and the smoothing of the trunk surface. Noise reduction is a difficult and complex process, due to different noise patterns from scan to scan. It

Table 1: Number and attributes of the sample trees.

Species	Number of trees		Range of diameters
	Training	Testing	at breast height (cm)
Oak	6	3	35 - 76
Beech	5	3	30 - 57
Wild cherry	2	1	22 - 33
Pine	1	1	34 - 57
Fir	2	1	23 - 45
Spruce	0	1	19
Total	16	10	

250 depends on the condition of the scanning environment and also the charac-  
 251 teristics of the trees. For example, we observed that when the trunk had  
 252 branches or small epicormic shoots, there was much of noise caused by the  
 253 multiple interceptions of the same laser beam by several branches and the  
 254 bark. This is the situation when a laser beam hits both the contour of the  
 255 branch and the bark resulting in a ghost point, with no reality, between the  
 256 branch and the bark (Figure 3 (a)). We observed that the point density in  
 257 noisy regions was often lower than in the relevant data regions. Thus, we  
 258 proposed a simple approach to remove noise by clustering the point cloud by  
 259 Euclidean distance with the idea that relevant data points are in the largest  
 260 cluster where the point density is highest. The choice of the threshold on the  
 261 minimal distance between clusters is critical. If the threshold is too small,  
 262 there is a risk that the relevant data would be removed, especially in the high  
 263 part of the trunk where the resolution is lower. After testing different values,

264 we set the threshold to 5 millimeters, which gave the best visual results for  
265 our scanning settings.

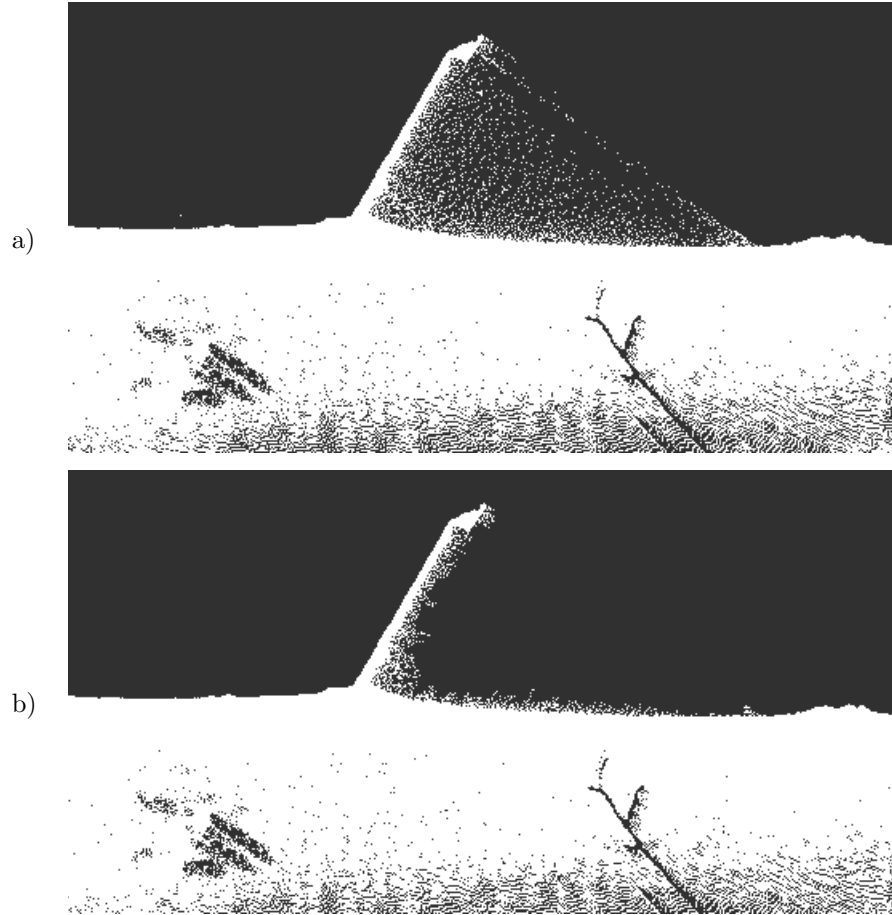


Figure 3: Noise processing for a wild cherry trunk. Point cloud before (a) and after (b) noise reduction process that only keeps the biggest cluster; the minimal distance between two clusters is 5 millimeters.

266 Due to the nature of a laser scan, the raw point cloud contains a cer-  
267 tain level of error. For example, the utilized scanner had a ranging er-  
268 ror of  $\pm 2$  millimeters at 10 meters. The smoothing step was performed

269 to reduce surface roughness caused by ranging uncertainty. However, the  
270 smoothing intensity was limited to maintain the bark roughness or defect  
271 shapes. The following steps were performed for smoothing and creating  
272 a mesh from the trunk point cloud using the Graphite software ([https://gforge.inria.fr/frs/?group\\_id=1465](https://gforge.inria.fr/frs/?group_id=1465)):  
273

- 274 1. Smooth the point cloud (Lévy and Bonneel, 2013) using only one it-  
275 eration with 30 neighbors. Only one iteration was used because with  
276 more iterations the smoothing process may erase defects with a weak  
277 relief.
- 278 2. Reconstruct the trunk surface (Boltcheva and Lévy, 2017) with the  
279 normal vector computed from 30 neighbors and the maximum distance  
280 used to connect neighbors of 5 millimeters. The radius value was chosen  
281 to be greater than the between-point distance in the point cloud but  
282 not too large to prevent the creation of wrong edges.
- 283 3. Smooth the created mesh by using the remesh smooth function (Lévy  
284 and Bonneel, 2013). The used parameter was the number of points  
285 similar to the one of the original point cloud.

## 286 2.5. *Segmentation of defects*

287 Our strategy to classify the defects on trunk surface was first to detect all  
288 potentially defective areas using a segmentation algorithm. The algorithm is  
289 an enhanced version of our previously published one (Nguyen et al., 2016b)  
290 that focuses on defects with little protuberance from tree bark. In this study,  
291 we proposed a preliminary step for segmenting tree branches. The motivation  
292 for developing this approach came from the existing links between a defect



293 present in the woody part and the impact of that defect on the bark surface,  
 294 expressed by a structured, and often protruding, irregularity. To detect these  
 295 irregularities, we defined the centerline of the trunk as a reference. In the  
 296 evaluation of the algorithm presented in Nguyen et al. (2016b), the presence  
 297 of branches was identified as an inconvenience for detecting smaller defects  
 298 in a branch vicinity. Thus, in this work, the branches were first segmented  
 299 by an algorithm that separates the points into two disjointed sets (illustrated  
 300 in Figure 4): (1) set  $T$  contains closer points to the trunk surface, and (2)  
 301 set  $B$  contains the branches according to the following algorithm.

- 302 • Estimation of the trunk radius  $r_m$ , using the mode of the distance to  
 303 the centerline of all points in the point cloud.
- 304 • Division of the point cloud volume into slices with a thickness of  $l$  mil-  
 305 limeter, following the centerline direction. Each slice was then divided  
 306 into angular sectors with an angle of  $\frac{l}{r_m}$  radian. The value of  $l$  should  
 307 be greater than the diameter of the largest branch. In our experiment,  
 308 the  $l$  parameter was set to values between 50 and 100 millimeters.
- 309 • For each angular sector, the nearest point to the center of the trunk  
 310 was added to set  $T$ , and the other points of the portion were added to  
 311 set  $B$ .
- 312 • For each point  $P$  in set  $T$ , we found subset  $S$  of set  $B$ , such as the  
 313 distance between point  $S_i \in S$  and  $P$  was less than or equal to  $\sqrt{2}l$ ,  
 314 and we moved them in set  $T$ . This algorithm assured that no point  
 315 on trunk surface left on the branches set  $B$  by accepting a branch part  
 316 with a length of  $\sqrt{2}l$  on the trunk set  $T$ .

317 After the branch segmentation, the original method (Nguyen et al., 2016b)  
 318 was applied to set  $T$  as follows. (i) For each point  $P$  in set  $T$ , we estimated  
 319 a reference point  $\hat{P}$  from a linear regression linking the radius variation to  
 320 longitudinal positions on a patch of neighboring points of  $P$ . (ii) The defect  
 321 points were detected by thresholding the difference between the distance from  
 322  $P$  and  $\hat{P}$ , denoted as  $(\delta)$ . (iii) The threshold was automatically computed  
 323 on the histogram of  $\delta$  using the Rosin's method (Rosin, 2001). Then, the  
 324 detected defect points were merged with set  $B$  containing the branches to  
 325 form a set of defect points  $D$ . The different potential defects were obtained  
 326 by clustering the defect points  $D$  by using Euclidean distance.

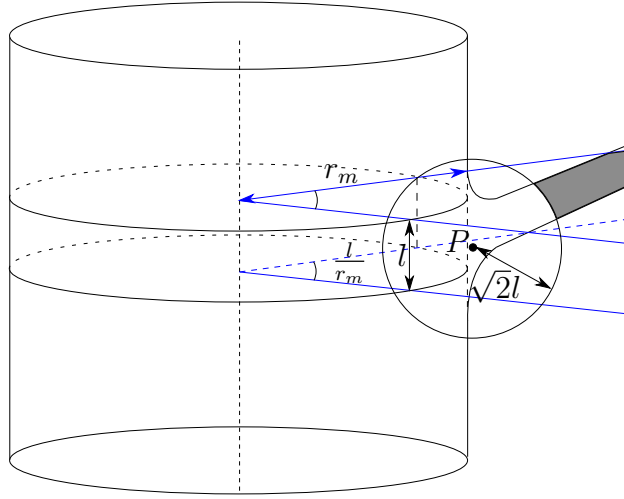


Figure 4: Illustration of the branch segmentation: the angular sector is defined by the volume inside planes formed by blue lines. The points in this angular sector that had a distance to  $P$  less than or equal to  $\sqrt{2}l$  were moved to the set of trunk points ( $T$ ). The set of branch points ( $B$ ) is in solid grey color.

## 327 2.6. Classification of defects

### 328 2.6.1. The random forests classifier

329 The random forests (Breiman, 2001) classifier is an ensemble classifier  
330 that aggregates a set of classification and regression trees (CARTs) (Breiman  
331 et al., 1984) to make a prediction. In the training step, all trees were built  
332 with the same parameters but on different subsets of the training samples.  
333 These subsets were generated from the training samples by a bootstrap sam-  
334 pling, which randomly selected the same number of vectors from the original  
335 set. The remaining "out-of-bag" (OOB) was used to compute the estimation  
336 error, which is known as the OOB error. Unlike CART, random forests does  
337 not consider all variables at each node to determine the best split threshold  
338 but a random subset of variables of the feature vector and the trees are built  
339 without pruning. The cardinality of the subset is an input parameter.

340 Another important parameter of the random forests classifier is the num-  
341 ber of trees, which must be sufficiently large to capture the full variability  
342 of the training data and yields good classification accuracy. One of the ad-  
343 vantages of the random forests classifier is that it does not overfit when  
344 increasing the number of trees at the expense of slower running time. In the  
345 classification step, random forests tested the feature vector, describing the  
346 new object with each tree in the forest. Each tree made a classification, or  
347 in other words, gave a vote for a class. The random forests classifier chose  
348 the class on which the majority of trees voted.

349 As mentioned above, the number of trees in the forest (*nbTrees*) and the  
350 number of variables (*nbVariables*) used to select and test for the best split  
351 when growing the trees are two important input parameters needed to train

the random forests classifier. The OOB error can be used to find the optimal value for these parameters. We ran an experiment with the *nbTrees* from 100 to 5,000 and the *nbVariables* from 1 to the number of variables of the feature vector. For each value of *nbVariables*, we could find the minimum value of *nbTrees*, which gave the minimum OOB error.

The random forests has been implemented in a number of free and open source libraries. In this study, we used the implementation in OpenCV-3.3 (Bradski, 2000). The advantage of OpenCV is its compatibility with the implementation of our algorithms in C++ programming language. The source code and sample data are available at the following GitHub repository: <https://github.com/vanthonguyen/trunkdefectclassification>

### 2.6.2. Feature vector

In this step, we used the defects detected by our segmentation algorithm and constructed the feature vector based on our expertise on the defects. Before computing the features, the point cloud of the defect was converted from Cartesian coordinate system to a custom coordinate system  $\{l, z, d\}$ , where  $l$  is the arc length computed from angle between the point and the plane  $Oxz$  and the distance from the point to the centerline,  $z$  is the height, and  $d$  is the difference between the distance and the reference distance from the point to the centerline (the distance between  $P$  and  $\hat{P}$  as presented in section 2.5). This conversion allowed us to measure the defect diameter along the curved surface of the trunk similar to a manual measurement. To reduce the inhomogeneity of point clouds due to the superimposition of data coming from several points of view or the non-uniform by TLS, the feature vector was computed from a subsampled point cloud. The subsampled point cloud

latter was computed by keeping only the closest point to the center of each voxel of a regular voxel grid of the defect point cloud. The voxel size was chosen by the average point spacing, which was 3 mm in our study. The following features were used:

1. Species:  $s$ .
2. Ratio between the number of points of the defect and the volume of its bounding box:  $c$  (equation 1)
3. Defect arc length:  $w = l_{max} - l_{min}$ .
4. Ratio between  $w$  and defect height:  $\frac{w}{h}$  where  $h$  equals  $z_{max} - z_{min}$ .
5. Ratio between  $w$  and maximum of  $d$ :  $\frac{w}{d_{max}}$ .
6. Mean of difference between the distance from  $P$  and  $\hat{P}$  for all points  $P$  of the defect:  $\bar{d}$ .
7. Standard deviation of the difference between the distance from  $P$  and  $\hat{P}$  for all points  $P$  of the defect:  $\sigma_d$ .
8. Hu moment invariants:  $I_1, I_2, I_3, I_4, I_5, I_6, I_7$  (see equations 4–10).
9. Ratio between the eigenvalue  $\lambda_1$  and the eigenvalue  $\lambda_3$ :  $\frac{\lambda_1}{\lambda_3}$ .
10. Ratio between the eigenvalue  $\lambda_2$  and the eigenvalue  $\lambda_3$ :  $\frac{\lambda_2}{\lambda_3}$ .
11. Angle between the eigenvector  $\vec{v}_3$  and the trunk axis at the height of defect:  $\alpha$ .

where  $\lambda_1$  is the eigenvalue associated with the eigenvector  $\vec{v}_1$  of the defect having the smallest angle, with the radial vector of the trunk at the center of the intersection between the defect and the trunk.  $\lambda_2$  is the eigenvalue associated with the eigenvector  $\vec{v}_2$  of the defect having the smallest angle with the tangential vector of the trunk at the center of the intersection between

401 the defect and the trunk.  $\lambda_3$  is the eigenvalue associated with the eigenvector  
 402  $\vec{v}_3$  of the defect having the smallest angle with the trunk axis at the height  
 403 of defect.

404 The species was an important variable because each one had a specific  
 405 bark roughness and a set of defects. For example, oak had burls but does  
 406 not had sphaeroblast, which was conversely related to beech. In addition,  
 407 for the same defect type, its shape could differ from one species to another.  
 408 For example, a branch scar on oak and on beech was very different.

409 Another relevant variable was the ratio between the number of points of  
 410 the defect and the volume of its bounding box, which measured the com-  
 411 pactness of the defect in the  $\{l, z, d\}$  coordinate system equation (1). This  
 412 feature could discriminate a flat defect and a significantly protruding defect.

$$c = \frac{\text{number of points}}{(l_{max} - l_{min})(z_{max} - z_{min})(d_{max} - d_{min})} \quad (1)$$

413 By using our expertise in the domain, the dimension was an important  
 414 criterion to classify defects, in particular small defects such as small burl and  
 415 bud cluster. For that reason, we included the arc length  $w$  as a feature. The  
 416 ratio  $\frac{w}{h}$  allowed us to distinguish between a branch scar and a bark zone,  
 417 which had a roughness higher than the local average on oak tree because the  
 418 branch scars often have width greater than height and bark zones have width  
 419 smaller than height. The ratio  $\frac{w}{d_{max}}$  helped to distinguish a flat object, such  
 420 as bark portion, branch scar and a more protruding one such as sphaeroblast  
 421 and picot. The mean and standard deviation of  $d$  were also included in the  
 422 feature vector because they help to distinguish between a branch scar and a  
 423 burl composed only of buds.

424 The Hu moment invariants (Hu, 1962) had good characteristics for the  
 425 object recognition because they were invariant with respect to translation,  
 426 scale, and rotation. The Hu moment invariants  $\{I_1, \dots, I_7\}$  were computed  
 427 from the normalized central moments  $nu_{ij}$  of orders  $(i + j) \geq 2$  and 3 (see  
 428 equations (3)–(10)).

$$mu_{ij} = \sum_{z,l} (z - \bar{z})^i (l - \bar{l})^j d \quad (2)$$

$$nu_{ij} = \frac{mu_{ij}}{mu_{00}^{(i+j)/2+1}} \quad (3)$$

$$I_1 = nu_{20} + nu_{02} \quad (4)$$

$$I_2 = (nu_{20} - nu_{02})^2 + 4nu_{11}^2 \quad (5)$$

$$I_3 = (nu_{30} - 3nu_{12})^2 + (3nu_{21} - nu_{03})^2 \quad (6)$$

$$I_4 = (nu_{30} + nu_{12})^2 + (nu_{21} + nu_{03})^2 \quad (7)$$

$$I_5 = (nu_{30} - 3nu_{12})(nu_{30} + nu_{12})[(nu_{30} + nu_{12})^2 - 3(nu_{21} + nu_{03})^2] + \\ (3nu_{21} - nu_{03})(nu_{21} + nu_{03})[3(nu_{30} + nu_{12})^2 - (nu_{21} + nu_{03})^2] \quad (8)$$

$$I_6 = (nu_{20} - nu_{02})[(nu_{30} + nu_{12})^2 - (nu_{21} + nu_{03})^2] + 4nu_{11}(nu_{30} + nu_{12})(nu_{21} + nu_{03}) \quad (9)$$

$$I_7 = (3nu_{21} - nu_{03})(nu_{30} + nu_{12})[(nu_{30} + nu_{12})^2 - 3(nu_{21} + nu_{03})^2] + \\ (3nu_{12} - nu_{30})(nu_{21} + nu_{03})[3(nu_{30} + nu_{12})^2 - (nu_{21} + nu_{03})^2] \quad (10)$$

429 The eigenvectors and eigenvalues of the defect were computed from a  
 430 principal component analysis (PCA) (Wold et al., 1987), which could be  
 431 useful for distinguishing between the defect with a long axis (branch) and  
 432 the flatter ones. Furthermore, because of the small number of branches in our

dataset, we did not distinguish between sequential branches and epicormic ones. Nevertheless, the angle between the eigenvector  $\vec{v}_1$  of defect and the trunk axis could be used to classify these types of branch on beech, oak and fir, as epicormic branches were quasi-perpendicular to the trunk axis, while sequential branches were more fastigiated.

### 2.6.3. Construction of the training dataset

We used both manually segmented and automatically segmented defects to train the random forests. The manual segmentation was done by using a home-made software (DGTalTools-Contrib), based on the library DGTal (DGTal). The software allowed us to select the faces on the mesh to define the footprints of the defects (Figure 5). Each defect was then saved in a separate file and used for training the random forests. We also trained the random forests using the results of our segmentation algorithm, along with the verification given by the shape of paper labels set in the vicinity of the defects and identifiable in the scan. Bark (no-defect) class was introduced even though it is not a defect type; they were bark zones with a roughness higher than the local average. These bark zones are often miss detected as a defect by the segmentation algorithm. This is concordant with our approach as the detection step was built to provide all potential zones of defects assuming the risk of false positive that could be eliminated in the classification step. The training database includes the following classes and the number of defects of each class is summarized in Table 2:

1. Branch, including sequential branch and epicormic branch.
2. Branch scar.
3. Burl.



- 458 4. Small defects, including picot, sphaeroblast, bud and bud cluster.  
 459 5. Bark.

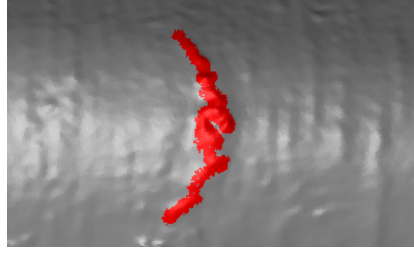


Figure 5: Manual segmentation of a defect

Table 2: Summary of the defects and barks encountered in the training set.

Species	Branch	Branch scar	Burl	Small defects	Bark
Oak	7	3	159	63	116
Beech	34	51	26	20	2
Wild Cherry	15	5	0	0	0
Pine	0	4	0	0	0
Fir	0	38	0	0	10
Total	56	101	185	83	128

#### 460 2.6.4. Performance evaluation criteria

461 To evaluate the performance of the classification algorithm, we used the  
 462 F-measure, a performance measurement, that is frequently used for classi-  
 463 fication problems. The F-measure is the harmonic mean of precision ( $PR$ )  
 464 and recall ( $RE$ ). We used the  $F_1$  score, mixing both with equal weights on  
 465  $PR$  and  $RE$ . The precision  $PR$  is the number of correctly classified positive

466 defects divided by the number of defects labeled by the system as positive  
 467 (equation (11)). The recall is the number of correctly classified positive de-  
 468 fects divided by the number of positive defects in the data (equation (12)).  
 469 On a binary classification problem, the  $F_1$  is defined by equation (equation  
 470 (13)).

$$PR = \frac{TP}{TP + FP} \quad (11)$$

$$RE = \frac{TP}{TP + FN} \quad (12)$$

471 where  $TP, FP, FN$  are true positive, false positive and false negative respec-  
 472 tively. Their definition is as follows:

- 473 •  $TP$  is the number of actual defects correctly classified as defect.
- 474 •  $FP$  is the number of non-defects incorrectly classified as defect.
- 475 •  $FN$  is the number of actual defects incorrectly classified as non-defect.

$$F_1 = 2 \frac{PR \cdot RE}{PR + RE} \quad (13)$$

476 For a multi-class classification problem, the F-measure must be extended  
 477 from the binary classification by an average of the F-measure of each class.  
 478 There are two approaches (Manning et al., 2008). One approach is the macro-  
 479 averaged F-measure (equation (14)), which is the unweighted mean of F-  
 480 measure for each label. The other is the micro-averaged F-measure (equation  
 481 (15)), which considers predictions from all instances together and calculate

the F-measure across all labels. Arithmetically, the micro-averaging favors bigger classes.

$$F_{m1} = \frac{\sum_{i=1}^n F_{1i}}{n} \quad (14)$$

$$F_{\mu 1} = 2 \frac{PR_{\mu} \cdot RE_{\mu}}{PR_{\mu} + RE_{\mu}} \quad (15)$$

$$PR_{\mu} = \frac{\sum_{i=1}^n TP_i}{\sum_{i=1}^n (TP_i + FP_i)} \quad (16)$$

$$RE_{\mu} = \frac{\sum_{i=1}^n TP_i}{\sum_{i=1}^n (TP_i + FN_i)} \quad (17)$$

where  $n$  is the number of classes.

We also used the confusion matrix (Provost and Kohavi, 1998) to evaluate the performance for a more detailed analysis of the misclassification between classes.

### 3. Results

In this section, we present the results of the segmentation algorithm followed by the results of the classification algorithm in comparison with the ground-truth data. We first present a global analysis of the performance related to exhaustiveness independently of the defect type focused on the differences coming from tree species. Then, the analysis of the results focuses on defect types independently of the species which are nevertheless considered in the discussion.

496 Table 3 shows the results of the segmentation algorithm for each individ-  
497 ual tree in the test database in terms of defect detection. We can see that  
498 the segmentation algorithm detected almost all of the defects, with 179 de-  
499 tected out of 183 (97.8%) in total. However, the number of false positives was  
500 very high (765), which will then be removed by the classification algorithm  
501 through a refined analysis of each detected areas. Moreover, Table 3 also  
502 shows that these false positives were mostly removed by the classification  
503 algorithm at the expense of some defects lost. The classification algorithm  
504 removed not only 694 (90.7%) false positives but also 28 (15.3%) actual de-  
505 fects.

506 We also observed that the segmentation algorithm produced more false  
507 positives on trees with furrowed barks, such as oak and pine, than on trees  
508 with smooth barks, such as beech and wild cherry. By contrast, the classi-  
509 fication algorithm removed the false positives more efficiently on trees with  
510 furrowed bark than on trees with smooth-bark. For example, in Table 3, we  
511 can see that on pine the number of false positives from the segmentation and  
512 classification are 105 and 2 respectively while on Beech 2 these numbers are  
513 70 and 12, respectively. The difference is illustrated in Figure 6.

Table 3: Results of the segmentation (seg.) and classification (cla.) steps compared with the observed defects.

Tree name	Observed	True positive		False positive		False negative	
		Seg.	Cla.	Seg.	Cla.	Seg.	Cla.
Oak 1	8	8	8	9	0	0	0
Oak 2	25	24	19	147	7	1	6
Oak 3	24	23	20	79	7	1	4
Beech 1	30	30	24	55	19	1	6
Beech 2	29	29	21	70	12	0	8
Beech 3	24	22	18	47	14	2	6
Wild Cherry	8	8	8	10	0	0	0
Pine	4	4	4	105	2	0	0
Fir	14	14	14	129	8	0	0
Spruce	17	17	15	114	2	0	4
Total	183	179	151	765	71	5	34

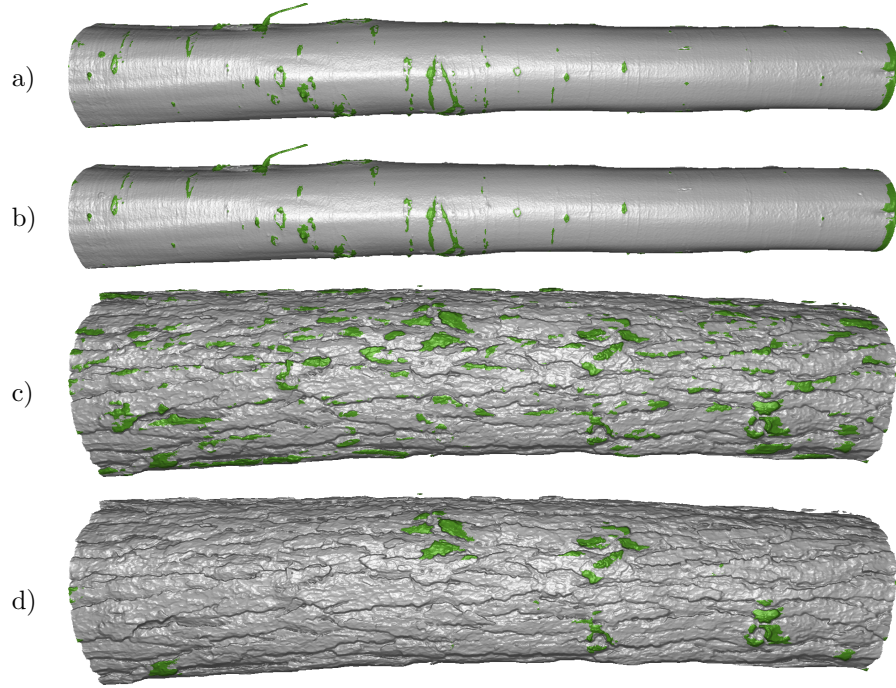


Figure 6: Defects detected by the segmentation algorithm (a, c) and refinement by the classification algorithm (b, d) for two logs: Beech 2 (a, b) and Pine (c, d).

514 Concerning the performance according to defect types, Figure 7 illustrates  
 515 classification results by coloring the mesh in agreement with the defect type.

516 Table 4 shows the performance criteria by defect types resulting from the  
 517 classification. The overall macro- and micro-averaged scores were 0.86 and  
 518 0.73, respectively. However, the algorithm did not perform equally well on all  
 519 classes of defect. The branch had the best  $F_1$  score of 0.89, followed by the  
 520 burl with an  $F_1$  score of 0.76. The algorithm performed less well on branch  
 521 scar and the small defect types with  $F_1$  scores of 0.61 and 0.46, respectively.

522 For allowing a better understanding of the differences, Figure 8 represents  
 523 the confusion matrix of the classification result. The matrix shows the match-

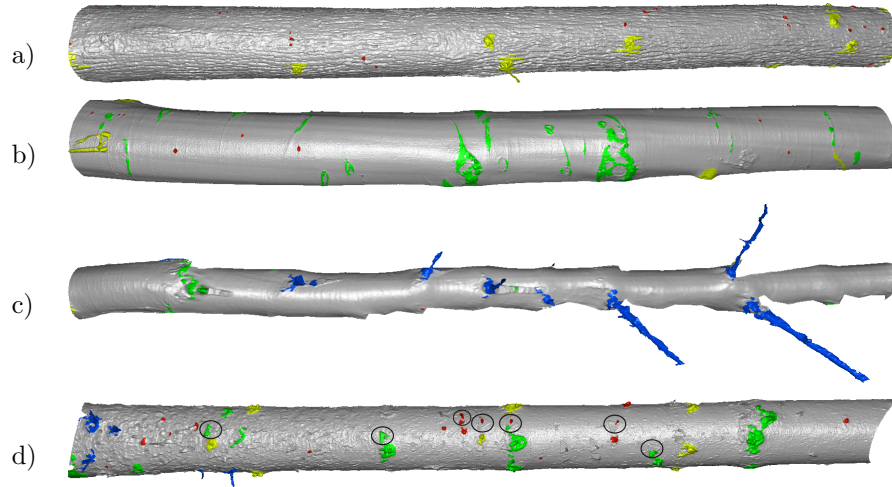


Figure 7: Examples of the classification results on the mesh of Oak 3 (a), Beech 1 (b), Wild cherry 3 (c), and Spruce (d). ■ is **Branch** type including both sequential and epicormic branches, ■ is **Branch scar**, ■ is Burl, ■ is **Small defect** including bud cluster, sphaeroblast and picot. On the mesh of the Spruce, the detected defects (circled) are the paper marks and pushpins that were used by the expert to mark the defect type before the scan was carried out. These false positives were ignored in our evaluation.

524 ing between predicted and observed defect types and allows a finer analysis  
 525 of the differences. We can see that one branch was classified as branch scar.  
 526 A more detailed analysis showed that it was a short dead stub branch of a  
 527 wild cherry (the large green region in Figure 7 (c)). Another branch was  
 528 classified as a burl because an epicormic branch is often originated from a  
 529 small burl, and the distinction by the algorithm is difficult in young develop-  
 530 ment stages. While the recall of the algorithm on the branch scar was very  
 531 high (0.84), the precision was not as good (0.48) because there were 49 bark  
 532 portions recognized as branch scar while there were 69 branch scars in total.  
 533 Some burls were confounded with the bark portions and small defects be-

Table 4: Precision, recall and  $F_1$  score of the different defect types

<b>Defect type</b>	<b>Precision</b>	<b>Recall</b>	<b><math>F_1</math></b>
Branch	1.00	0.80	0.89
Branch scar	0.48	0.84	0.61
Burl	0.73	0.81	0.76
Small defect	0.56	0.39	0.46
Bark	0.95	0.90	0.93
Beech (micro avg.)	0.70	0.70	0.70
Beech (macro avg.)	0.70	0.70	0.70
Oak (micro avg.)	0.90	0.90	0.90
Oak (macro avg.)	0.66	0.68	0.67
All (micro avg.)	0.86	0.86	0.86
All (macro avg.)	0.75	0.74	0.73

534 cause a burl consisting of only buds may have a similar look to a small defect  
 535 (see Figure 1 (i) and (j)) or a bark portion since both are quite flat. The  
 536 confusion matrix shows that the small defects were often confounded with  
 537 bark portions and branch scars. It is to be noted that the number of bark  
 538 portions miss-classified as small defects was 15 and the number of small de-  
 539 fects miss-classified as bark portions was 16. There was only one branch scar  
 540 miss-classified as small defect but 11 small defects miss-classified as branch  
 541 scars.

542 Although no spruce data were used to train the random forests, the predic-  
 543 tions on this spruce (Figure 7 (d)) were good, as 15 out of 18 were detected.  
 544 However, two branch scars were detected as small defects and two branch



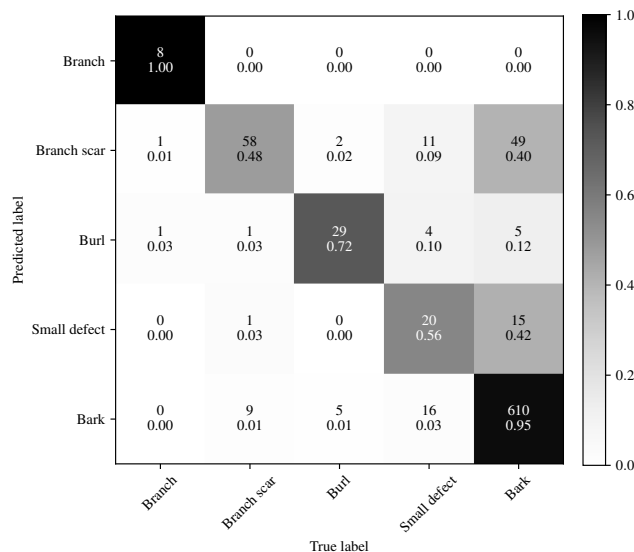


Figure 8: Confusion matrix with the absolute value and normalized value (precision). The color of cells is a function of normalized value.

scars were detected as burls.

## 4. Discussion

### 4.1. Defect detection

In summary, our algorithms had a very good performance in defect detection, even with the small defects corresponding to a slight modification of the bark roughness. These good results are both due to the robust estimation of the trunk centerline, and the fitting on a local longitudinal patch, of the regular radius variation, allowing for the calculation a local reference distance. Our approach outperforms the detection based on a radius resulting from the fitting of geometrical primitives such as circle or cylinders proposed in other works (Thomas et al., 2007; Kretschmer et al., 2013) especially for cross-sections with less circular shape as already discussed in Nguyen et al.

(2016b). It is clear that several factors can impact the detection, such as scan resolution and quality and missing data resulting from occlusion. Our algorithm can detect small defects such as picot which often have a diameter between 0.5 centimeter and 1 centimeter, thus outperforming all previous works with size ranging from 7.5 centimeters (Thomas et al., 2007) to 2.0 centimeters (Kretschmer et al., 2013). Moreover, Kretschmer et al. (2013) only focused on the branch scars and their method was not automatic.

Because of their shapes, French and North American foresters have named large branch scars of beech and wild cherry trees "Chinese mustache" (or eyebrow). It often covers a large peripheral area, and the two parts of the mustache are often thin. This may result in an over-segmentation (Figure 9 (a)). Two or more large defects can also be close enough to form a large shape. Although the human eye will dissociate the large shape as multiple separated defects, the algorithm saw it as a defect, which consequently created an under-segmentation (Figure 9 (b)). The under-segmentation can also occur on the trunk of conifer in the case of connected branch scars (Figure 9 (c)).

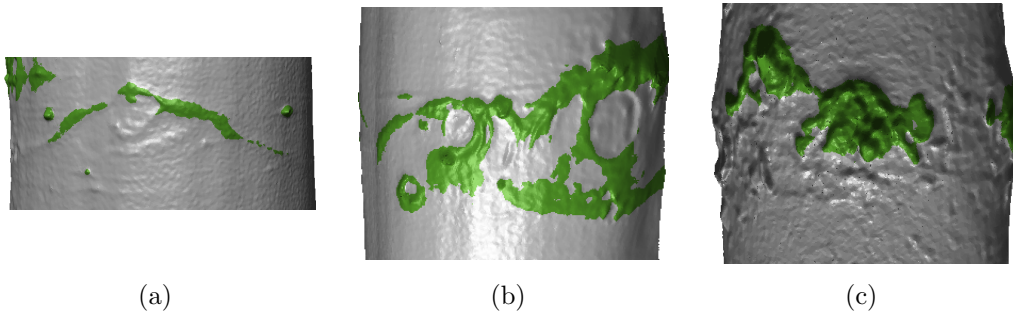


Figure 9: Examples of over-segmentation on beech (a), under-segmentation on beech (b) and on spruce (c). Within each image, all connected green areas belong to the same defect.

572

573 As the segmentation is the step preceding the classification, the perfor-

574 mance of the classification algorithm also depends on the performance of  
 575 the segmentation step. Thus, any improvement in segmentation will result  
 576 in a better classification. The most important parameters were the patch  
 577 size and the bin width of the histogram used to find the threshold by the  
 578 Rosin’s method (Rosin, 2001), and the voxel size used to compute the cen-  
 579 terline. Their choices were described in detail in Nguyen et al. (2016a). As  
 580 mentioned earlier, the over and under-segmentation can occur in the seg-  
 581 mentation step especially through the defect clustering through a Euclidean  
 582 distance filter. These errors can affect the classification, and consequently,  
 583 the assessment of the tree quality. In addition to the influence of misclassifi-  
 584 cation, the over-segmentation increased the number of defects and decreased  
 585 their dimension. By contrast, the under-segmentation decreased the number  
 586 of defects and increased their dimensions.

#### 587 *4.2. Defect classification*

588 Visually, we can see that our algorithms were able to detect and classify  
 589 most of the defects (Figure 7), including small defects such as picot and bud  
 590 clusters. Based on Table 4, the overall classification result was good, with  
 591 a micro-averaged  $F_1$  score of 0.86 and a macro-averaged score of 0.73. The  
 592 result was promising, particularly on the classification of branch and burl.  
 593 However, we did not obtain a very high  $F_1$  score (0.46) on the small defect  
 594 because, first, we could not totally remove all the false positives and, second,  
 595 there was some confusion between the classes due to the very high intra-class  
 596 variability and the interclass similarity.

597 For example, the confusion between branch scars and burls can be ex-  
 598 plained by the fact that some burls containing only buds have a shape that

looks like a branch scar because both are flat. In the field, human eyes can easily distinguish these two defect types; however, in the point cloud or mesh, it could be difficult to distinguish them. For small-sized defects, the confusion between burls and small defects can merely be explained by the initial definition of burl and small defect. When a burl is composed only of buds it might have a similar shape to a bud cluster. In our database, small defect types include several biological defect types: a bud cluster with less than six buds, sphaeroblast, and picot. A bud cluster may have a shape similar to a small burl. The confusion was high, even for expert eyes.

With the objective of wood quality assessment, subclasses considering the size of defects with the same biological origin can be useful to refine the analysis in future studies but need a suitable assessment of the defect characteristics by algorithms, which is beyond the scope of this paper. More generally, it addresses the problem of a combination of defects that occurs rather frequently because they have the same origin and correspond to different stages of development or because they result from a spatial proximity, as in examples illustrating under-segmentation in Figure 9. Improvements could be a more refined algorithm for merging close protruding areas and a detailed definition of the defect types, adding size classes linked to the resulting quality impact as already mentioned.

#### 4.2.1. *Influence of species and bark roughness*

As a non-intuitive result (coming from the easier visual assessment of the defects on smooth bark), a lower  $F_1$  score was observed on beech compared with oak (Table 4). In the segmentation step, on trees with furrowed bark, there were many more false positives, resulting of the misdetection of bark

624 portions as defects. This is in agreement with our hypothesis. However, the  
 625 false positives on trees with furrowed bark had a common shape created by  
 626 the pattern of the rhytidome, and they were easily detectable and removed  
 627 by the classification through the definition of the Bark class. In contrast, on  
 628 trees with smooth bark, the false positives were created by bark portions,  
 629 very similar to actual defects in terms of protrusion and spatial distribution.  
 630 Moreover, on species with smooth bark, and particularly on beech, we also  
 631 observed many wrinkles or cambium alterations revealed by the elliptical  
 632 shape (*Nectria* disease) of bark (Figure 10). These alterations were often  
 633 misclassified by our algorithm as branch scars rather logically in the absence  
 634 of more relevant type definition corresponding to these singularities. Thus,  
 635 the classification algorithm has a higher performance on furrowed bark trees  
 636 than on smooth bark trees.

#### 637 4.2.2. *Parameters of random forests and future improvements*

638 Random forests have only two principal parameters: the number of trees  
 639 in the forest (*nbTrees*) and the number of variables (*nbVariables*) used to  
 640 select and test for the best split when growing the trees. Their performance  
 641 was slightly influenced by the number of trees if it was chosen sufficiently  
 642 high (1,000 trees in our experiment). With the number of trees over 1,000,  
 643 the performance gain was minimal. *nbVariables* was chosen following the  
 644 OpenCV recommendation, which was  $\sqrt{variables}$ . We also noticed that  
 645 random forests are very robust to over-fitting so the feature selection is less  
 646 critical. Random forests can give a good performance, even with a small  
 647 training dataset (Rodriguez-Galiano et al., 2012); however, it depends also  
 648 on the intra-class variability of the defect class. Because burl and branch scar

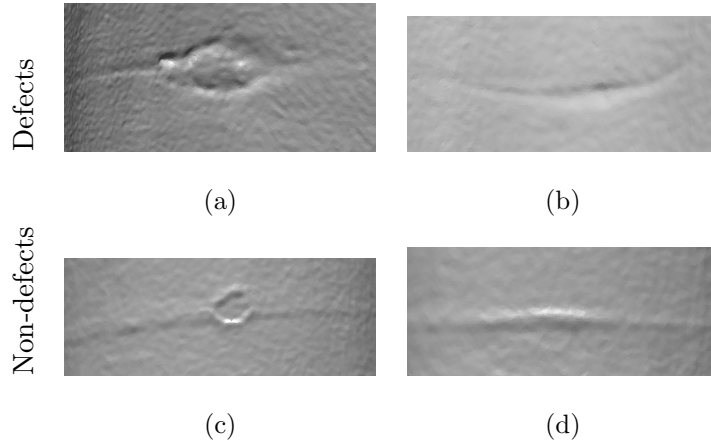


Figure 10: Examples of equivalent bark appearances considered either to be a branch scar ((a) and (b)) or a non-defect ((c) and (d)). This has been determined according to our own biological expertise. This figure illustrates the difficulty distinguish between defects and non-defects. The region in (c), while having a shape similar to a branch scar as in (a), is a scar resulting from slight damages due to *Nectria* attack affecting just the bark and not the wood below. The region in (d) has been considered as non-defect since it was formed by the covering of a dead bud during the very first years of tree development with no consequence for the wood quality.

649 have a high intra-class variability, in future work, we would like to add more  
 650 training data of these types. As the incident angle of laser beams changes  
 651 with the different heights of the trunk, it is also important to have the defect  
 652 data from different trunk heights.

653 Another suggestion to improve the performance of the classification is to  
 654 remove species in the feature vector and separately train random forests for  
 655 each species, considering that the information on the species is a prerequisite  
 656 brought by an operator or by another identification step (Othmani et al.,  
 657 2013). This approach might have a better performance but requires more

658 training data. Our test carried out with data of the most present species  
659 (beech) in our database did not clearly outperform random forests trained  
660 with all species. The  $F_{\mu 1}$  were 0.71 for random forests trained with only  
661 beech defects and 0.70 for random forests trained with all species defects.

#### 662 4.3. *Use for grading trunk quality*

663 The performance of defect classification can influence the grading result  
664 of standing trees. Nonetheless, the impact of the misclassification of class  
665 on the quality assessment is difficult to assess. The most important is the  
666 classification of large defects. Once there is an occurrence of these large  
667 defects, the occurrence of smaller defects is less important. However, in the  
668 case of highest quality trunk, the classification performance is more critical  
669 because one misclassification, even of a small defect, can result in a change  
670 to a higher or lower quality class. Thus, a further development of the current  
671 method is needed to measure the defect dimension which is required to assess  
672 the impact of defects by a standard (AFNOR, 1999a,b, 2012).

673 Regarding the current scanning setting, the spatial resolution does not  
674 allow for classifying between a picot and a less important small defect, such  
675 as bud cluster. Only one picot is allowed in the case of highest quality trunk.  
676 Thus, in the case that there is only the occurrence of small defects, an addi-  
677 tional expert inspection could be suggested to verify the classification result  
678 in the case of high commercial value. Beyond grading issues, the informa-  
679 tion about defect type and position on the log can be used to optimize the  
680 transformation, with the objective of increasing the volume of high-quality  
681 products but such exceeds the scope of this paper even if it is a real prospect.

682 As a common problem for the remote sensing technologies, the quality of

683 TLS data can be limited by the occlusion, especially when there are branches  
684 on the trunk or false positive created by moss (*Musci L.*) or lichens. In  
685 general, scanning the tree from multiple views can reduce occlusions, as the  
686 occlusion on the high part of the tree is difficult to avoid.

## 687 5. Conclusions

688 In this paper, we have presented a random forests-based classifier to iden-  
689 tify defects on trunk surface from TLS data. The potential defects were  
690 detected by our segmentation algorithm (Nguyen et al., 2016b). Each de-  
691 tected defect was then classified into one of the four defect classes or bark  
692 using the random forests classifier. Our experiment showed that from the  
693 high-density data acquired by TLS, we can detect and classify most of the  
694 defects on tree bark. The overall  $F_{\mu 1}$  score of the classification algorithm was  
695 0.86. These preliminary results are thus very promising. We could further  
696 improve the score with the addition of more data and with the definition  
697 of defect subclasses considering not only their biological type but also their  
698 size and impact on wood quality. An interesting option will be to train the  
699 random forests separately for each tree species. The information about the  
700 defect type in addition to its dimension and position can be used to assess  
701 the quality of roundwood or standing tree. This is the first step towards  
702 developments for helping experts in the assessment of the quality of standing  
703 trees or timber logs in forests or for enhancing the knowledge coming from  
704 true shape scanners in the primary wood processing industry.



## 705 **Acknowledgments**

706 This work was supported by the French National Research Agency through  
707 the Laboratory of Excellence ARBRE (ANR-12-LABXARBRE-01) and by  
708 the Lorraine French Region. We would like to thank Florian Vast for provid-  
709 ing technical support and for scanning and measuring the trees used in this  
710 research.

## 711 **References**

- 712 AFNOR, 1999a. EN 1927-1 - Classement qualitatif des bois ronds résineux -  
713 Partie 1 : épicéas et sapins  
714 Qualitative classification of softwood round timber - Part 1 : Spruces and  
715 firs.
- 716 AFNOR, 1999b. EN 1927-2 - Classement qualitatif des bois ronds résineux  
717 - Partie 2 : pins  
718 Qualitative classification of softwood round timber - Part 2 : Pines.
- 719 AFNOR, 2012. EN 1316-1 - Bois ronds feuillus - Classement qualitatif -  
720 Partie 1: Chêne et hêtre  
721 Hardwood round timber - Qualitative classification - Part 1: Oak and  
722 beech.
- 723 Aguilera, C., Sanchez, R., Baradit, E., 2008. Detection of knots using X-ray  
724 tomographies and deformable contours with simulated annealing. Wood  
725 Res. 53, 57–66.

- 726 Astrup, R., Ducey, M.J., Granhus, A., Ritter, T., von Lüpke, N., 2014.  
727 Approaches for estimating stand-level volume using terrestrial laser scan-  
728 ning in a single-scan mode. *Can. J. For. Res* 44, 666–676. doi:10.1139/  
729 cjfr-2013-0535.
- 730 Bishop, C.M., 1995. *Neural Networks for Pattern Recognition*. Oxford Uni-  
731 versity Press, Inc., New York, NY, USA.
- 732 Blanchette, D., Fournier, R.A., Luther, J.E., Côté, J.F., 2015. Predicting  
733 wood fiber attributes using local-scale metrics from terrestrial lidar data:  
734 A case study of newfoundland conifer species. *For. Ecol. Manage.* 347, 116  
735 – 129. doi:10.1016/j.foreco.2015.03.013.
- 736 Boltcheva, D., Lévy, B., 2017. Surface reconstruction by computing restricted  
737 voronoi cells in parallel. *Computer-Aided Design* 90, 123–134. doi:10.  
738 1016/j.cad.2017.05.011.
- 739 Bradski, G., 2000. *The OpenCV Library*. Dr. Dobb’s Journal of Software  
740 Tools .
- 741 Breiman, L., 2001. Random forests. *Mach. Learn.* 45, 5–32. doi:10.1023/A:  
742 1010933404324.
- 743 Breiman, L., Friedman, J., Stone, C.J., Olshen, R.A., 1984. *Classification*  
744 *and regression trees*. Wadsworth Int Group, Belmont, CA.
- 745 Chehata, N., Guo, L., Mallet, C., 2009. Airborne lidar feature selection for  
746 urban classification using random forests. *Int. arch. photogramm. remote*  
747 *sens. spat. inf. sci.* 38, 207–212.

748 Colin, F., Mecherghi, R., Dhôte, J.F., Fontaine, F., 2010a. Epicormic on-  
749 togeny on quercus petraea trunks and thinning effects quantified with the  
750 epicormic composition. *Ann. For. Sci.* 67, 813–813. doi:10.1051/forest/  
751 2010049.

752 Colin, F., Mothe, F., Freyburger, C., Morisset, J.B., Leban, J.M., Fontaine,  
753 F., 2010b. Tracking rameal traces in sessile oak trunks with X-ray computer  
754 tomography: Biological bases, preliminary results and perspectives. *Trees-*  
755 *Struc. Func.* 24, 953–967. doi:10.1007/s00468-010-0466-1.

756 Cortes, C., Vapnik, V., 1995. Support-vector networks. *Mach. Learn.* 20,  
757 273–297. doi:10.1007/BF00994018.

758 Dassot, M., Colin, A., Santenoise, P., Fournier, M., Constant, T., 2012.  
759 Terrestrial laser scanning for measuring the solid wood volume, includ-  
760 ing branches, of adult standing trees in the forest environment. *Comput.*  
761 *Electron. Agric.* 89, 86 – 93. doi:10.1016/j.compag.2012.08.005.

762 Dassot, M., Constant, T., Fournier, M., 2011. The use of terrestrial lidar  
763 technology in forest science: Application fields, benefits and challenges.  
764 *Ann. For. Sci.* 68, 959–974. doi:10.1007/s13595-011-0102-2.

765 Devroye, L., Györfi, L., Lugosi, G., 1996. A Probabilistic Theory of Pat-  
766 tern Recognition. Springer New York, New York, NY. doi:10.1007/  
767 978-1-4612-0711-5.

768 DGtal, . DGtal: Digital Geometry tools and algorithms library. [http:](http://dgtal.org)  
769 [//dgtal.org](http://dgtal.org).

- 770 Díaz-Uriarte, R., De Andres, S.A., 2006. Gene selection and classification of  
771 microarray data using random forest. *BMC Bioinform.* 7. doi:10.1186/  
772 1471-2105-7-3.
- 773 Fink, S., 1999. *Pathological and Regenerative Plant Anatomy*. Schweizerbart  
774 Science Publishers, Stuttgart, Germany.
- 775 Fonseca, M.A., 2005. *The measurement of roundwood: methodologies and*  
776 *conversion ratios*. CABI Publishing, Wallingford, Oxfordshire, UK.
- 777 Gardiner, B., Moore, J., 2014. Creating the wood supply of the fu-  
778 ture, in: Fenning T. (eds) *Challenges and Opportunities for the World's*  
779 *Forests in the 21st Century*. Springer, pp. 677–704. doi:10.1007/  
780 978-94-007-7076-8\_30.
- 781 Gislason, P., Benediktsson, J., Sveinsson, J., 2006. Random forests for land  
782 cover classification. *Pattern Recognit. Lett.* 27, 294–300. doi:10.1016/j.  
783 patrec.2005.08.011.
- 784 Guo, L., Chehata, N., Mallet, C., Boukir, S., 2011. Relevance of airborne lidar  
785 and multispectral image data for urban scene classification using random  
786 forests. *ISPRS J. Photogramm. Remote Sens.* 66, 56–66. doi:10.1016/j.  
787 isprsjprs.2010.08.007.
- 788 Hopkinson, C., Chasmer, L., Young-Pow, C., Treitz, P., 2004. Assessing  
789 forest metrics with a ground-based scanning lidar. *Can. J. For. Res* 34,  
790 573–583. doi:10.1139/x03-225.
- 791 Hu, M.K., 1962. Visual pattern recognition by moment invariants. *IRE*

792 Transactions on Information Theory 8, 179–187. doi:10.1109/TIT.1962.  
793 1057692.

794 Kankare, V., Joensuu, M., Vauhkonen, J., Holopainen, M., Tanhuanpää,  
795 T., Vastaranta, M., Hyyppä, J., Hyyppä, H., Alho, P., Rikala, J., et al.,  
796 2014. Estimation of the timber quality of scots pine with terrestrial laser  
797 scanning. *Forests* 5, 1879–1895. doi:10.3390/f5081879.

798 Krähenbühl, A., Kerautret, B., Debled-Rennesson, I., Longuetaud, F.,  
799 Mothe, F., 2012. Knot detection in X-ray CT images of wood, in:  
800 International Symposium on Visual Computing, Springer. pp. 209–218.  
801 doi:10.1007/978-3-642-33191-6\_21.

802 Krähenbühl, A., Roussel, J.R., Kerautret, B., Debled-Rennesson, I., Mothe,  
803 F., Longuetaud, F., 2016. Robust knot segmentation by knot pith tracking  
804 in 3d tangential images, in: International Conference on Computer Vision  
805 and Graphics, Springer. pp. 581–593. doi:10.1007/978-3-319-46418-3\_  
806 52.

807 Kretschmer, U., Kirchner, N., Morhart, C., Spiecker, H., 2013. A new ap-  
808 proach to assessing tree stem quality characteristics using terrestrial laser  
809 scans. *Silva Fenn.* 47, 1–14. doi:10.14214/sf.1071.

810 Lévy, B., Bonneel, N., 2013. Variational anisotropic surface meshing with  
811 voronoi parallel linear enumeration, in: Proceedings of the 21st in-  
812 ternational meshing roundtable. Springer, pp. 349–366. doi:10.1007/  
813 978-3-642-33573-0-21.

- 814 Li, P.L.P., a.L. Abbott, Schmoldt, D., 1996. Automated analysis of CT  
815 images for the inspection of hardwood logs, in: Proceedings of Interna-  
816 tional Conference on Neural Networks (ICNN'96), IEEE. pp. 1744–1749.  
817 doi:10.1109/ICNN.1996.549164.
- 818 Lin, W., Wang, J., 2012. An integrated 3D log processing optimization sys-  
819 tem for hardwood sawmills in central Appalachia, USA. *Comput. Electron.*  
820 *Agric.* 82, 61–74. doi:10.1016/j.compag.2011.12.014.
- 821 Longuetaud, F., Mothe, F., Kerautret, B., Krähenbühl, A., Hory, L., Leban,  
822 J., Debled-Rennesson, I., 2012. Automatic knot detection and measure-  
823 ments from X-ray CT images of wood: A review and validation of an  
824 improved algorithm on softwood samples. *Comput. Electron. Agric.* 85, 77  
825 – 89. doi:10.1016/j.compag.2012.03.013.
- 826 Luther, J.E., Skinner, R., Fournier, R.A., van Lier, O.R., Bowers, W.W.,  
827 Côté, J.F., Hopkinson, C., Moulton, T., 2014. Predicting wood quantity  
828 and quality attributes of balsam fir and black spruce using airborne laser  
829 scanner data. *Forestry* 87, 313–326. doi:10.1093/forestry/cpt039.
- 830 Maltamo, M., Peuhkurinen, J., Malinen, J., Vauhkonen, J., Packalén, P.,  
831 Tokola, T., et al., 2009. Predicting tree attributes and quality charac-  
832 teristics of scots pine using airborne laser scanning data. *Silva Fenn.* 43,  
833 507–521.
- 834 Manning, C.D., Raghavan, P., Schütze, H., 2008. Introduc-  
835 tion to Information Retrieval. Cambridge University Press. chap-

836 ter 13. p. 280. URL: [https://nlp.stanford.edu/IR-book/](https://nlp.stanford.edu/IR-book/information-retrieval-book.html)  
837 [information-retrieval-book.html](https://nlp.stanford.edu/IR-book/information-retrieval-book.html), doi:10.1017/CB09780511809071.

838 Microtec, 2019. CT Log. URL: [https://microtec.eu/en/catalogue/](https://microtec.eu/en/catalogue/products/ctlog)  
839 [products/ctlog](https://microtec.eu/en/catalogue/products/ctlog). Last visited on 2019/02/10.

840 Müller, F., Jaeger, D., Hanewinkel, M., 2019. Digitization in wood supply –  
841 A review on how Industry 4.0 will change the forest value chain. *Comput.*  
842 *Electron. Agric.* 162, 206–218. doi:10.1016/j.compag.2019.04.002.

843 Mutanga, O., Adam, E., Cho, M.A., 2012. High density biomass estima-  
844 tion for wetland vegetation using worldview-2 imagery and random for-  
845 est regression algorithm. *Int. J. Appl. Earth Obs. Geoinf.* 18, 399–406.  
846 doi:10.1016/j.jag.2012.03.012.

847 Nguyen, V.T., Kerautret, B., Debled-Rennesson, I., Colin, F., Piboule,  
848 A., Constant, T., 2016a. Algorithms and implementation for segment-  
849 ing tree log surface defects, in: *International Workshop on Reproducible*  
850 *Research in Pattern Recognition*, Springer. pp. 150–166. doi:10.1007/  
851 978-3-319-56414-2\_11.

852 Nguyen, V.T., Kerautret, B., Debled-Rennesson, I., Colin, F., Piboule, A.,  
853 Constant, T., 2016b. Segmentation of defects on log surface from terres-  
854 trial lidar data, in: *Pattern Recognition (ICPR), 2016 23rd International*  
855 *Conference on*, IEEE. pp. 3168–3173. doi:10.1109/ICPR.2016.7900122.

856 Niemeyer, J., Rottensteiner, F., Soergel, U., 2014. Contextual classification  
857 of lidar data and building object detection in urban areas. *ISPRS J. Pho-*

858 togramm. Remote Sens. 87, 152–165. doi:10.1016/j.isprsjprs.2013.  
859 11.001.

860 Othmani, A., Voon, L.F.L.Y., Stolz, C., Piboule, A., 2013. Single tree species  
861 classification from terrestrial laser scanning data for forest inventory. Pat-  
862 tern Recognit. Lett. 34, 2144–2150. doi:10.1016/j.patrec.2013.08.004.

863 Pickens, J.B., Throop, S.A., Friendewey, J.O., 1997. Choosing Prices to  
864 Optimally Buck Hardwood Logs with Multiple Log-Length Demand Re-  
865 strictions. For. Sci. 43, 403–413. doi:10.1093/forestscience/43.3.403.  
866 publisher: Narnia.

867 Provost, F., Kohavi, R., 1998. Glossary of terms. journal of machine learning  
868 30, 271–274. doi:10.1023/A:1017181826899.

869 Pyörälä, J., Kankare, V., Vastaranta, M., Rikala, J., Holopainen, M., Sipi,  
870 M., Hyypä, J., Uusitalo, J., 2018. Comparison of terrestrial laser scanning  
871 and X-ray scanning in measuring Scots pine (*Pinus sylvestris* L.) branch  
872 structure. Scand. J. For. Res. 33, 291–298. doi:10.1080/02827581.2017.  
873 1355409.

874 Racko, V., 2013. Verify the accuracy of estimation the model between  
875 dimensional characteristics of branch scar and the location of the knot in  
876 the beech trunk. Annals of Warsaw Univ. of Life Sciences-SGGW. Forestry  
877 & Wood Technology 84.

878 Jörg Elektronik GmbH, 2019. JORO-X: X-ray scanner - Detection of internal  
879 wood qualities. URL: <https://www.je-gmbh.de/en/Products/JORO-X>.  
880 Last visited on 2019/02/10.



- 881 Rodriguez-Galiano, V.F., Ghimire, B., Rogan, J., Chica-Olmo, M., Rigol-  
882 Sanchez, J.P., 2012. An assessment of the effectiveness of a random forest  
883 classifier for land-cover classification. *ISPRS J. Photogramm. Remote Sens.*  
884 67, 93–104. doi:10.1016/j.isprsjprs.2011.11.002.
- 885 Rosin, P.L., 2001. Unimodal thresholding. *Pattern Recognit.* 34, 2083–2096.  
886 doi:10.1016/S0031-3203(00)00136-9.
- 887 Schütt, C., Aschoff, T., Winterhalder, D., Thies, M., Kretschmer, U.,  
888 Spiecker, H., 2004. Approaches for recognition of wood quality of standing  
889 trees based on terrestrial laserscanner data, in: *Proceedings of the IS-*  
890 *PRS working group VIII/2, Freiburg, Germany. International Archives of*  
891 *Photogrammetry, Remote Sensing, and Spatial Information Sciences*, pp.  
892 179–182.
- 893 Simonse, M., Aschoff, T., Spiecker, H., Thies, M., 2003. Automatic de-  
894 termination of forest inventory parameters using terrestrial laserscanning,  
895 in: *Proceedings of the ScandLaser Scientific Workshop on Airborne Laser*  
896 *Scanning of Forests*, pp. 252–258.
- 897 Stängle, S.M., Brüchert, F., Kretschmer, U., Spiecker, H., Sauter, U.H., 2014.  
898 Clear wood content in standing trees predicted from branch scar measure-  
899 ments with terrestrial lidar and verified with X-ray computed tomography  
900 1. *Can. J. For. Res* 44, 145–153. doi:10.1139/cjfr-2013-0170.
- 901 Terzopoulos, D., Fleischer, K., 1988. Deformable models. *Vis Comput.* 4,  
902 306–331. doi:10.1007/BF01908877.

903 Thomas, L., Shaffer, C.A., Mili, L., Thomas, E., 2007. Automated detection  
904 of severe surface defects on barked hardwood logs. *For. Prod. J.* 57, 50–56.

905 Thomas, L., Thomas, R.E., 2010. A graphical automated detection sys-  
906 tem to locate hardwood log surface defects using high-resolution three-  
907 dimensional laser scan data, in: *Proceedings of the 17th Central Hardwood*  
908 *Forest Conference*, pp. 92–101.

909 Thomas, R.E., 2009. Modeling the relationships among internal defect fea-  
910 tures and external Appalachian hardwood log defect indicators. *Silva Fenn.*  
911 43, 447–456.

912 Van Leeuwen, M., Hilker, T., Coops, N.C., Frazer, G., Wulder, M.A., Newn-  
913 ham, G.J., Culvenor, D.S., 2011. Assessment of standing wood and fiber  
914 quality using ground and airborne laser scanning: a review. *For. Ecol.*  
915 *Manage.* 261, 1467–1478. doi:10.1016/j.foreco.2011.01.032.

916 Van Leeuwen, M., Nieuwenhuis, M., 2010. Retrieval of forest structural  
917 parameters using lidar remote sensing. *Eur. J. For. Res.* 129, 749–770.  
918 doi:10.1007/s10342-010-0381-4.

919 Wold, S., Esbensen, K., Geladi, P., 1987. Principal component analysis.  
920 *Chemom. Intell. Lab. Syst* 2, 37–52. doi:10.1016/0169-7439(87)80084-9.

921 Yao, T., Yang, X., Zhao, F., Wang, Z., Zhang, Q., Jupp, D., Lovell, J.,  
922 Culvenor, D., Newnham, G., Ni-Meister, W., et al., 2011. Measuring  
923 forest structure and biomass in New England forest stands using echidna  
924 ground-based lidar. *Remote Sens. Environ.* 115, 2965–2974. doi:10.1016/  
925 j.rse.2010.03.019.

- 926 Yuan, F., Sawaya, K.E., Loeffelholz, B.C., Bauer, M.E., 2005. Land  
927 cover classification and change analysis of the Twin Cities (Minnesota)  
928 Metropolitan Area by multitemporal Landsat remote sensing. Remote  
929 Sens. Environ. 98, 317–328. doi:10.1016/j.rse.2005.08.006.
- 930 Zhu, D., Connors, R.W., Schmoldt, D.L., Araman, P.a., 1996. A prototype  
931 vision system for analyzing CT imagery of hardwood logs. IEEE Trans.  
932 Syst. Man. Cybern. B Cybern. 26, 522–532. doi:10.1109/3477.517028.